Deployment of Privacy-Preserving Machine Learning for Political Polling in the 2024 Presidential Election

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PPML Workshop

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Overview

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- We build a system for securely predicting political preferences from web browsing data

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- We collect and analyze data from almost 8000 unique users
- All analysis takes place under MPC

Roadmap

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1. Motivation

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2. System Design

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2. System Design
3. Learning Algorithm

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2. System Design
3. Learning Algorithm
4. Lessons Learned and Future Directions

Motivation

Background

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- Web browsing behavior can predict voting results

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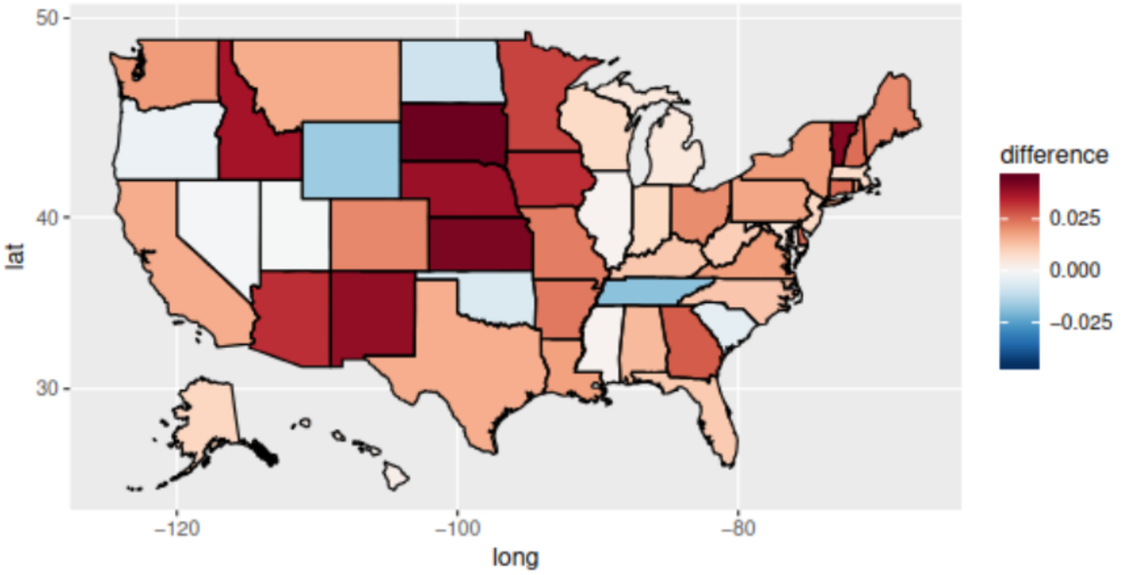
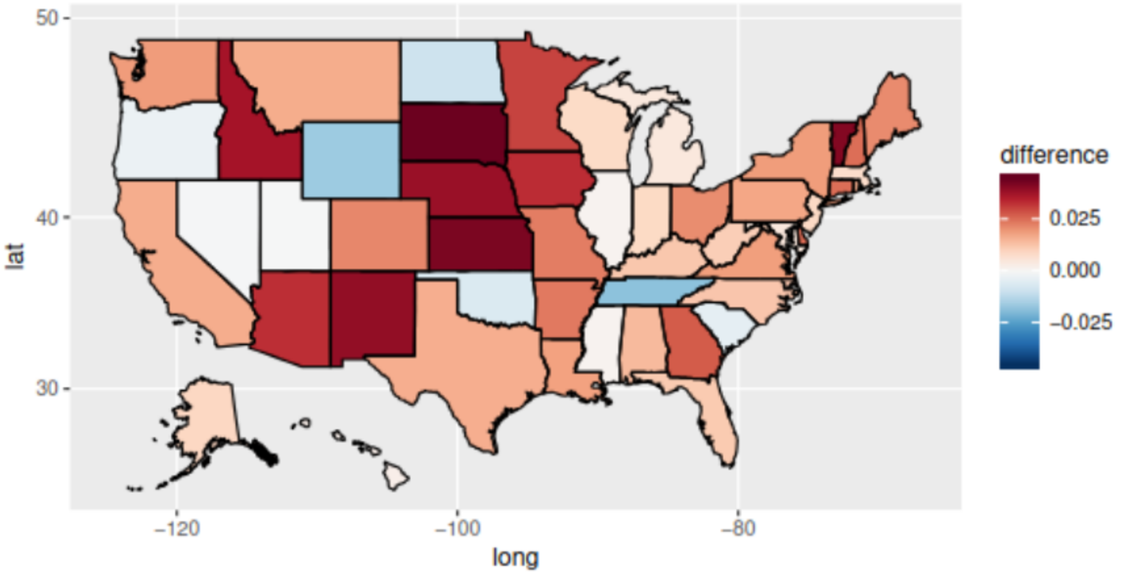


Figure 8: Impact of the 'Comey letter' at the state level.

Background

- Web browsing behavior can predict voting results
- Quantifying the 'Comey letter' (Comarela et al.)
  - The event was too close to the election for other polling methods to detect the effect



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West Virginia 2024 Presidential Election Polls

Harris vs. Trump

Source	Date	Sample	Harris	Trump	Other
Research America	8/30/2024	400 LV ±4.9%	34%	61%	5%

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Michigan 2024 Presidential Election Polls

Instantly compare a poll to prior one by same pollster

Harris vs. Trump

Source	Date	Sample	Harris	Trump	Other
Average of 23 Polls†			**48.6%**	**46.8%**	-
FAU / Mainstreet	11/04/2024	713 LV	49%	47%	4%
Emerson College	11/04/2024	790 LV ±3.4%	50%	48%	2%
Research Co.	11/04/2024	450 LV ±4.6%	49%	47%	4%
InsiderAdvantage	11/03/2024	800 LV ±3.7%	47%	47%	6%
Trafalgar Group	11/03/2024	1,079 LV ±2.9%	47%	48%	5%
MIRS / Mich. News Source	11/03/2024	585 LV ±4%	50%	48%	2%
NY Times / Siena College	11/03/2024	998 LV ±3.7%	47%	47%	6%
Morning Consult	11/03/2024	1,108 LV ±3%	49%	48%	3%
AtlasIntel	11/02/2024	1,198 LV ±3%	48%	50%	2%
Redfield & Wilton	11/01/2024	1,731 LV ±2.2%	47%	47%	6%
The Times (UK) / YouGov	11/01/2024	942 LV ±3.9%	48%	45%	7%
EPIC-MRA	11/01/2024	600 LV ±4%	48%	45%	7%
Marist Poll	11/01/2024	1,214 LV ±3.5%	51%	48%	1%
AtlasIntel	10/31/2024	1,136 LV ±3%	49%	49%	2%
Echelon Insights	10/31/2024	600 LV ±4.4%	48%	48%	4%
MIRS / Mich. News Source	10/31/2024	1,117 LV ±2.5%	47%	49%	4%
UMass Lowell	10/31/2024	600 LV ±4.5%	49%	45%	6%
Washington Post	10/31/2024	1,003 LV ±3.7%	47%	46%	7%
Fox News	10/30/2024	988 LV ±3%	49%	49%	2%
CNN	10/30/2024	726 LV ±4.7%	48%	43%	9%
Suffolk University	10/30/2024	500 LV ±4.4%	47%	47%	6%

Two Approaches to Political Polling

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Traditional Polling

- Slow
- Expensive
- Coarse-grained insights

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Web Behavior Analysis

- Immediate
- Cheap
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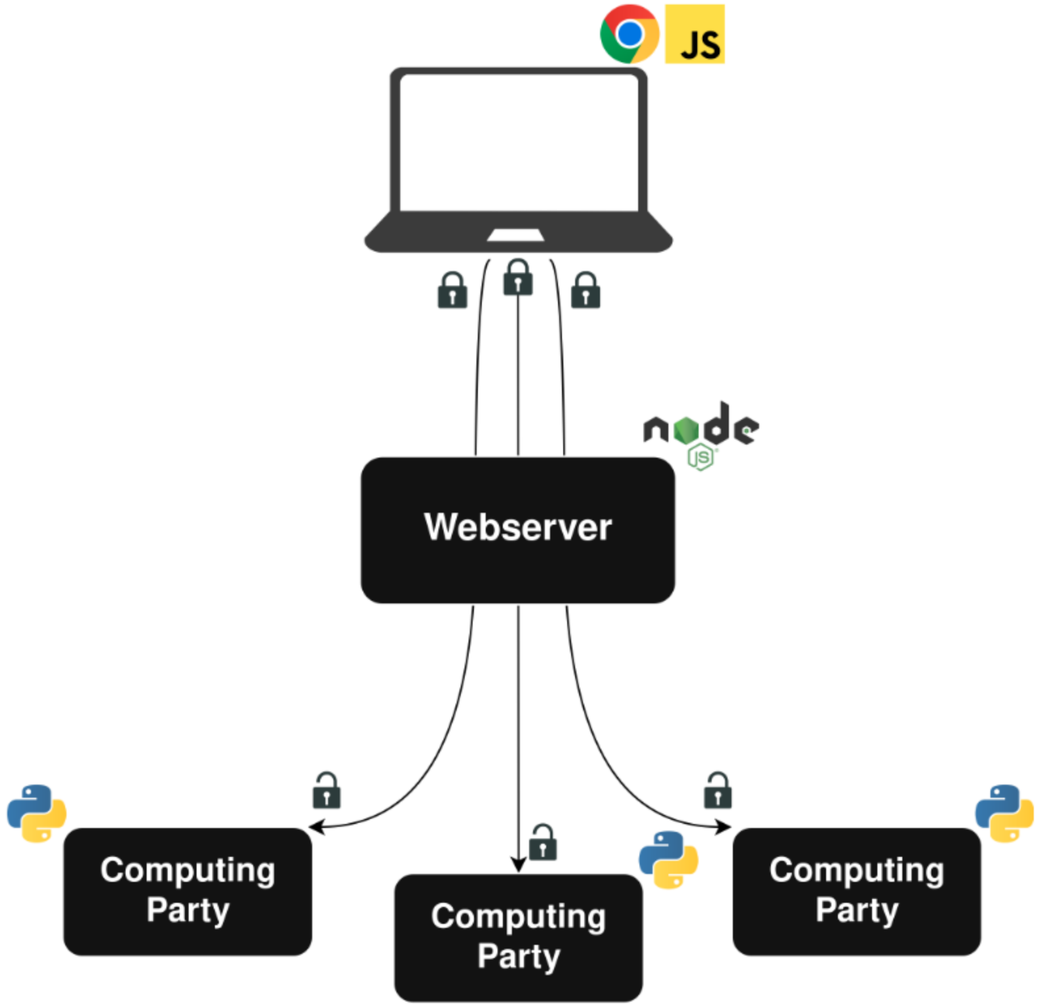
What about privacy?

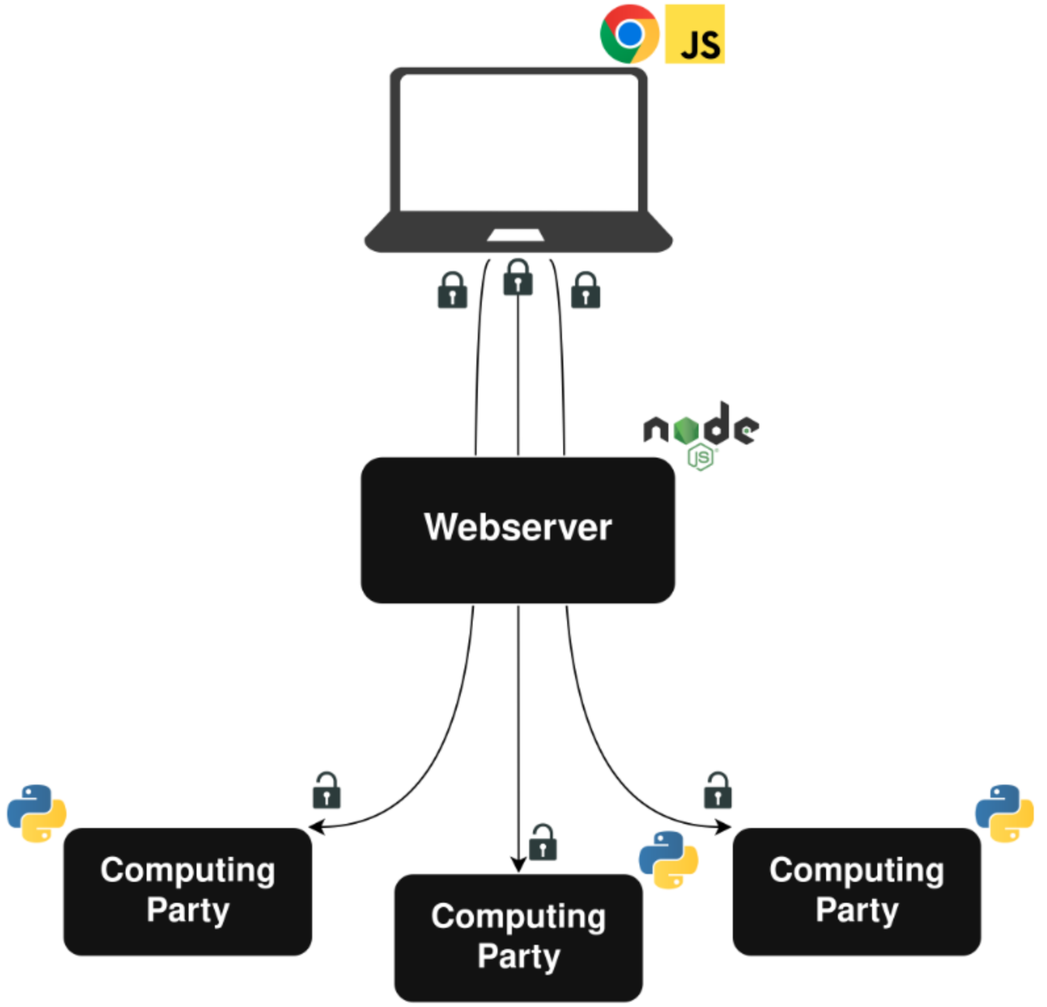
System Design

Three Components



Three Components

- Client Plugin



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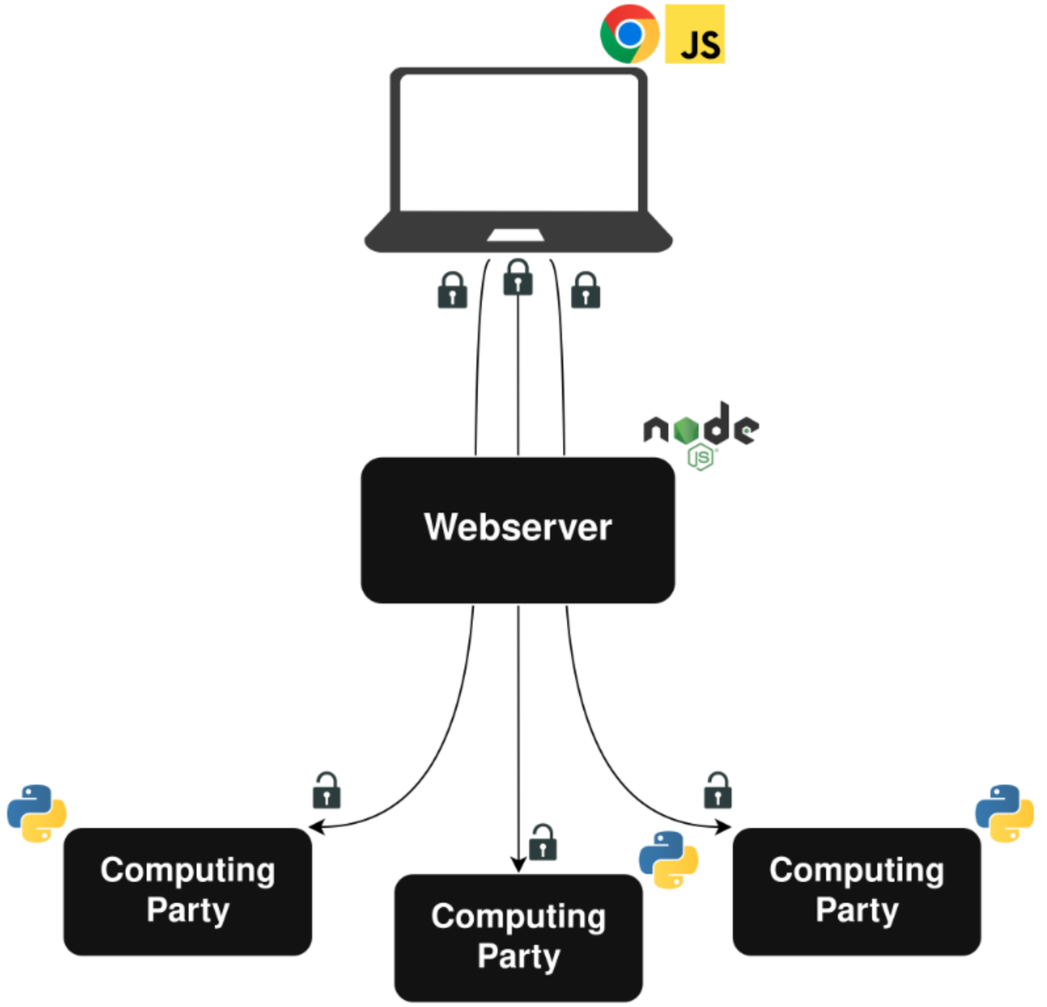
- Client Plugin

- Webserver



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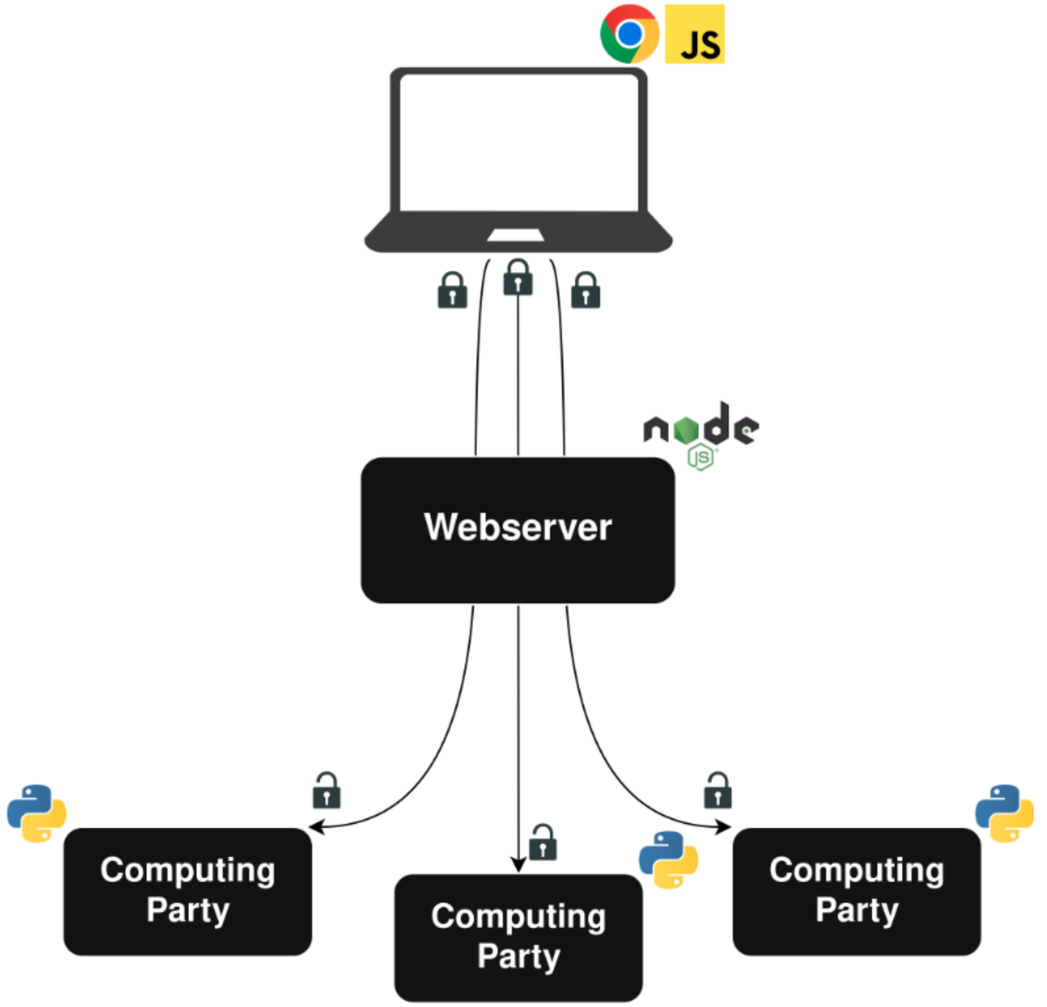

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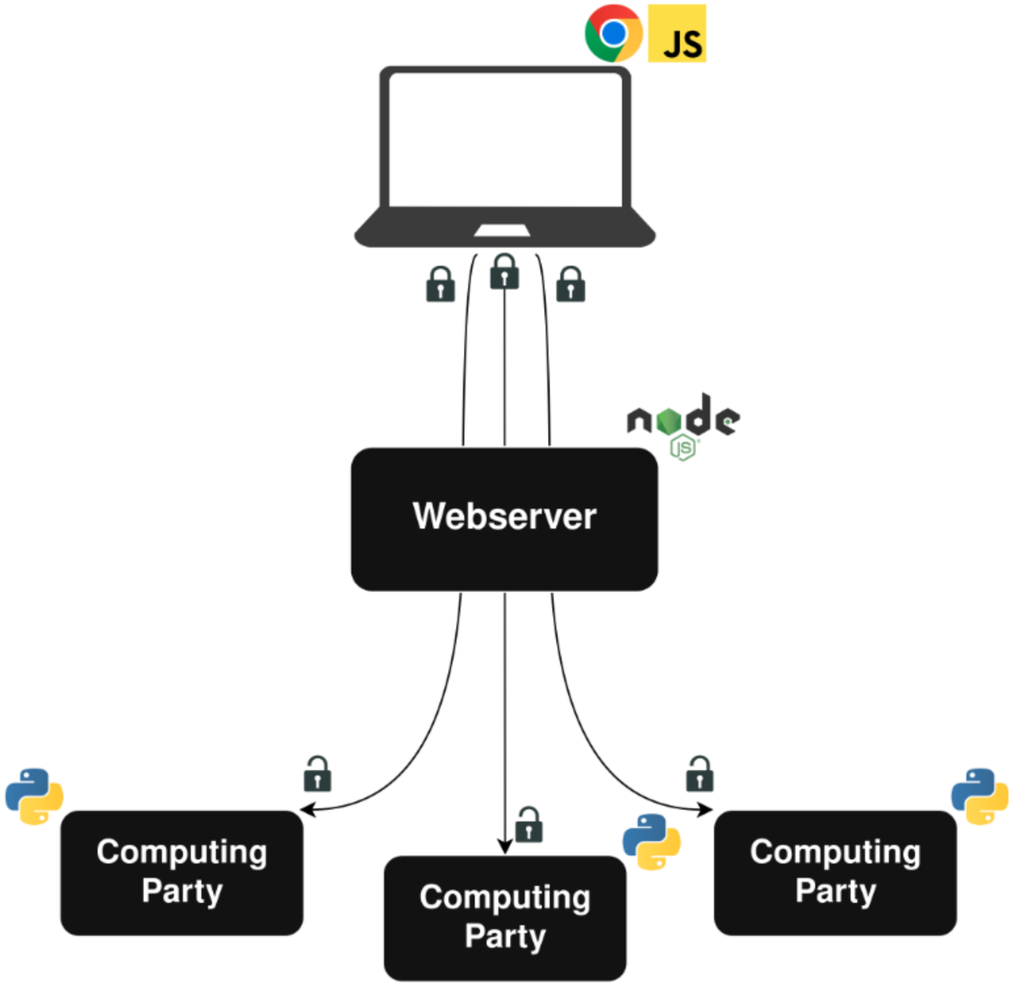

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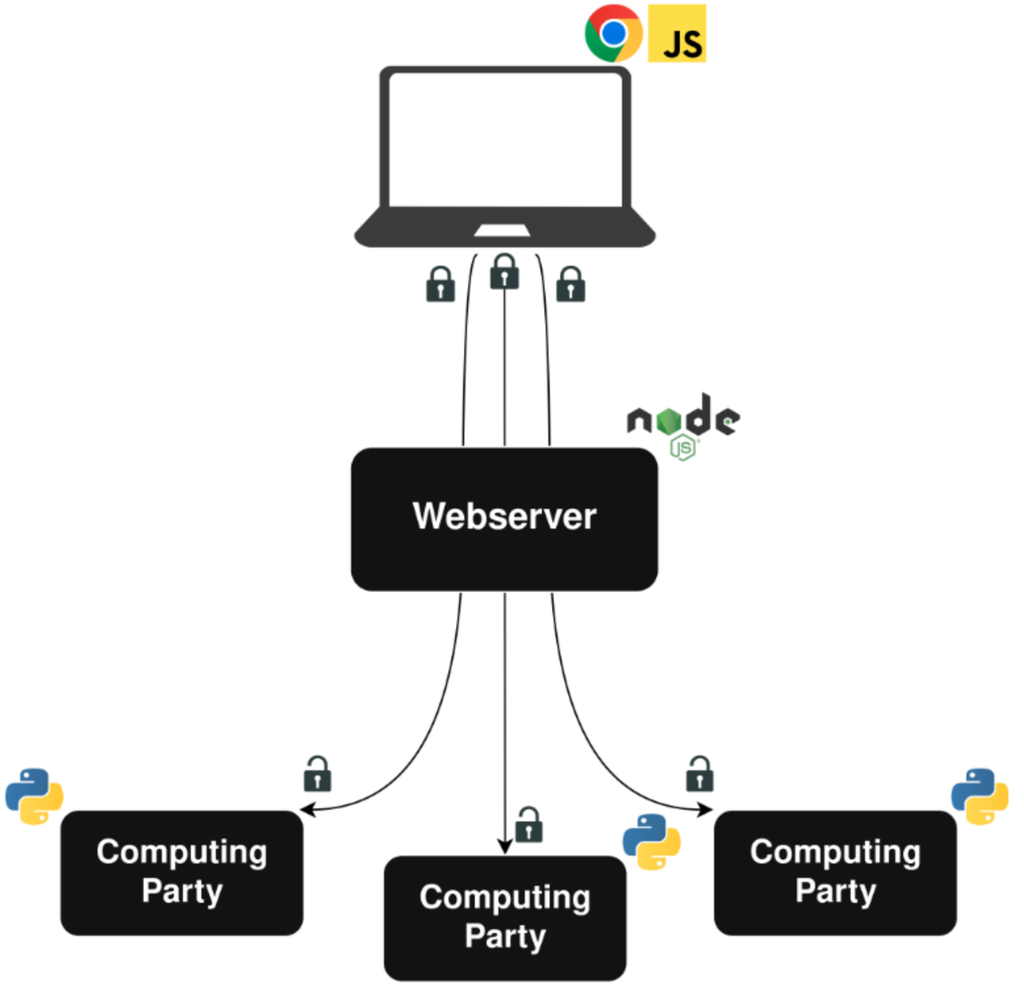

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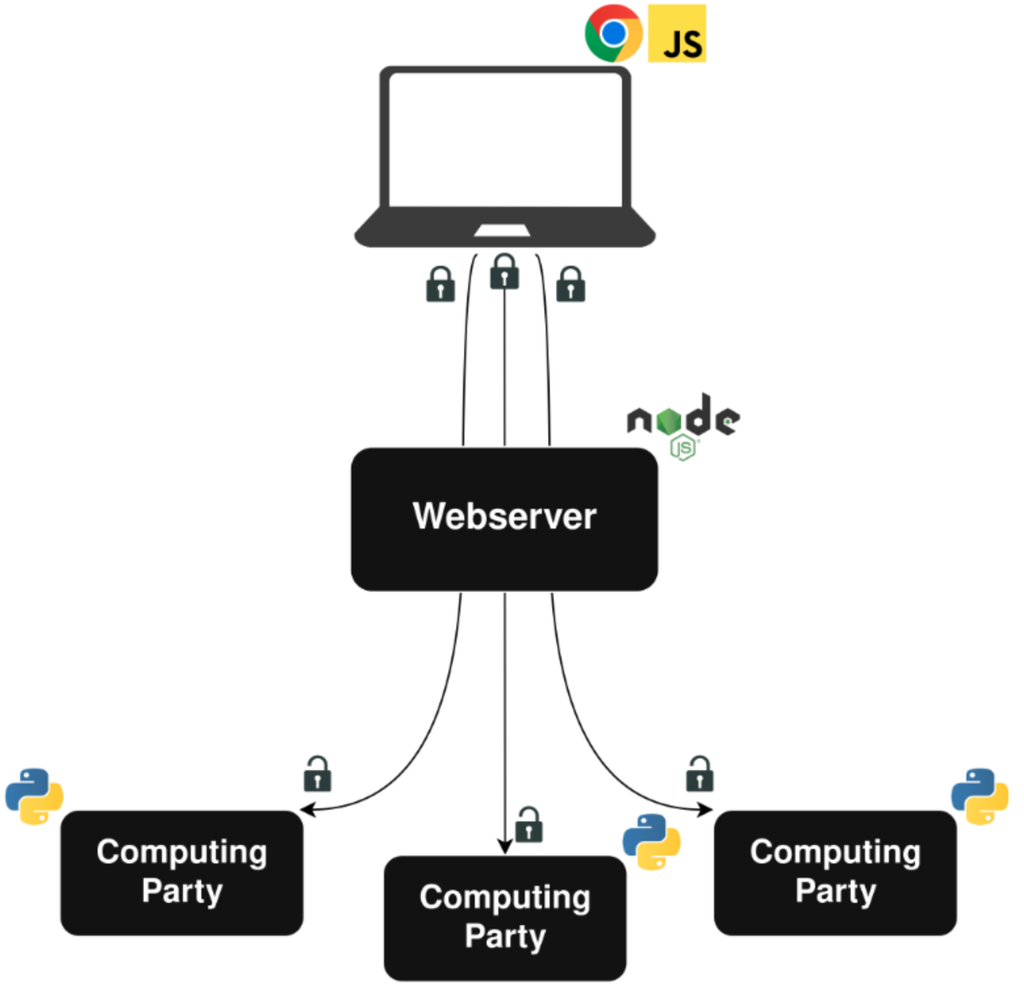

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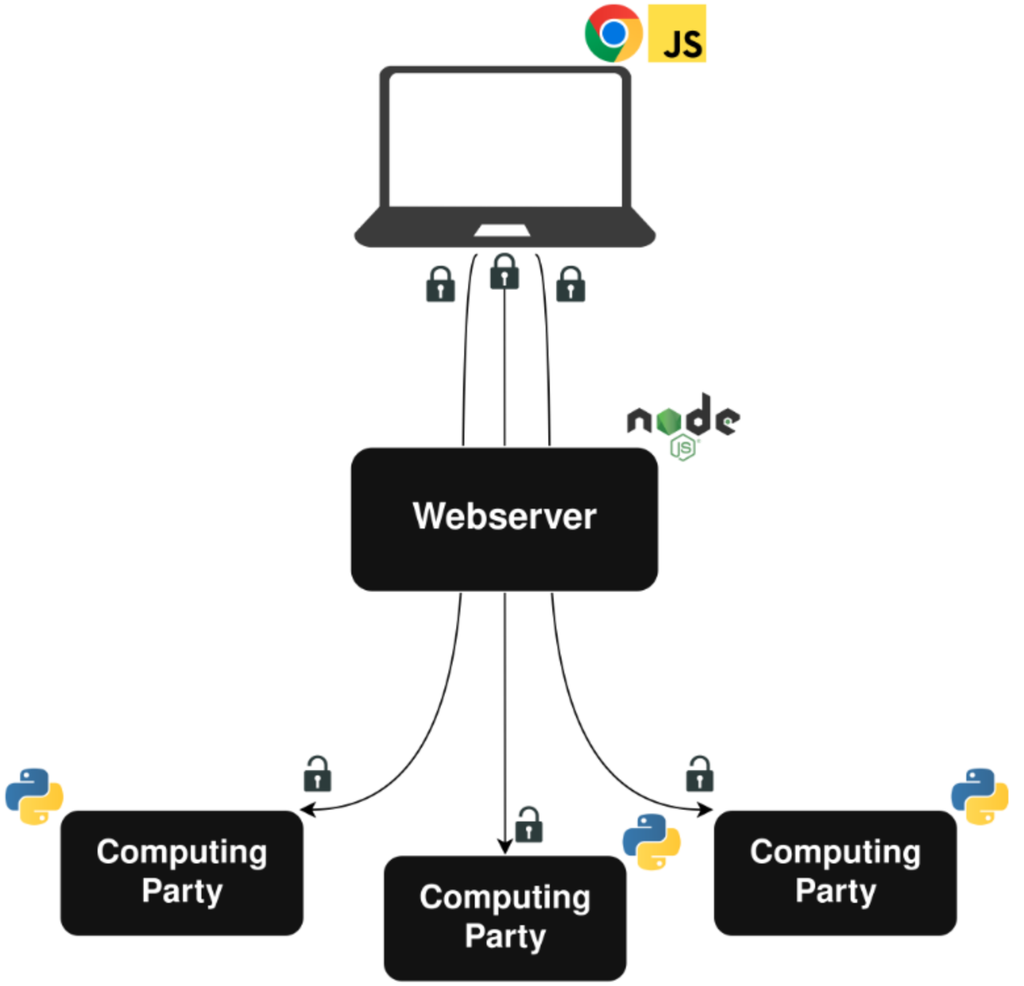

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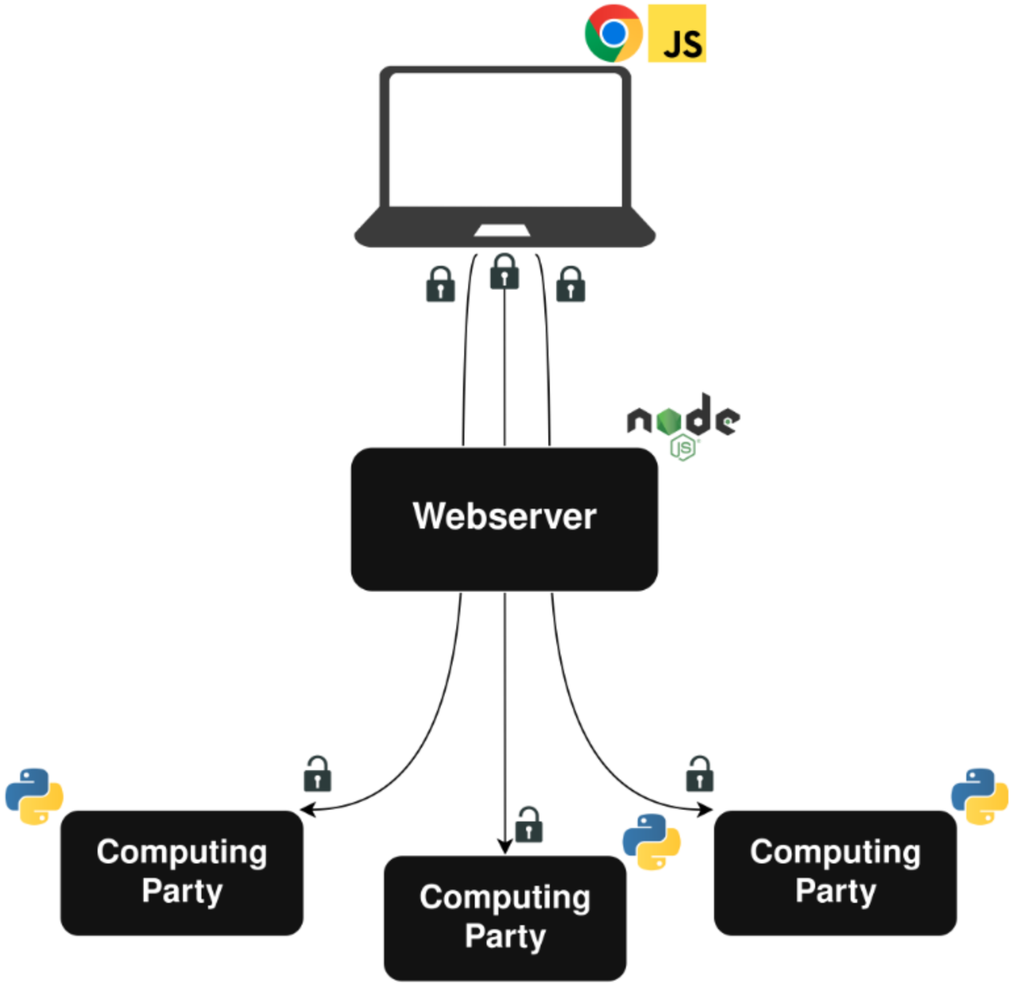

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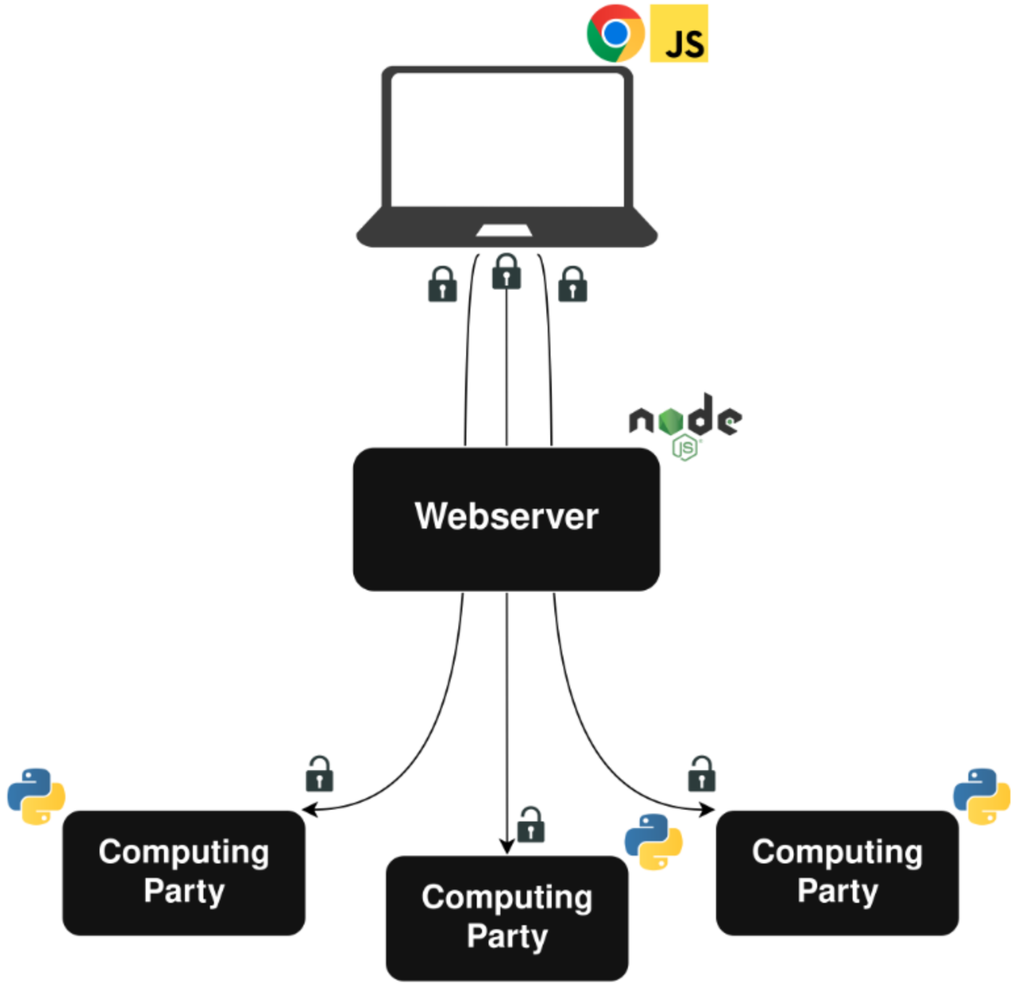

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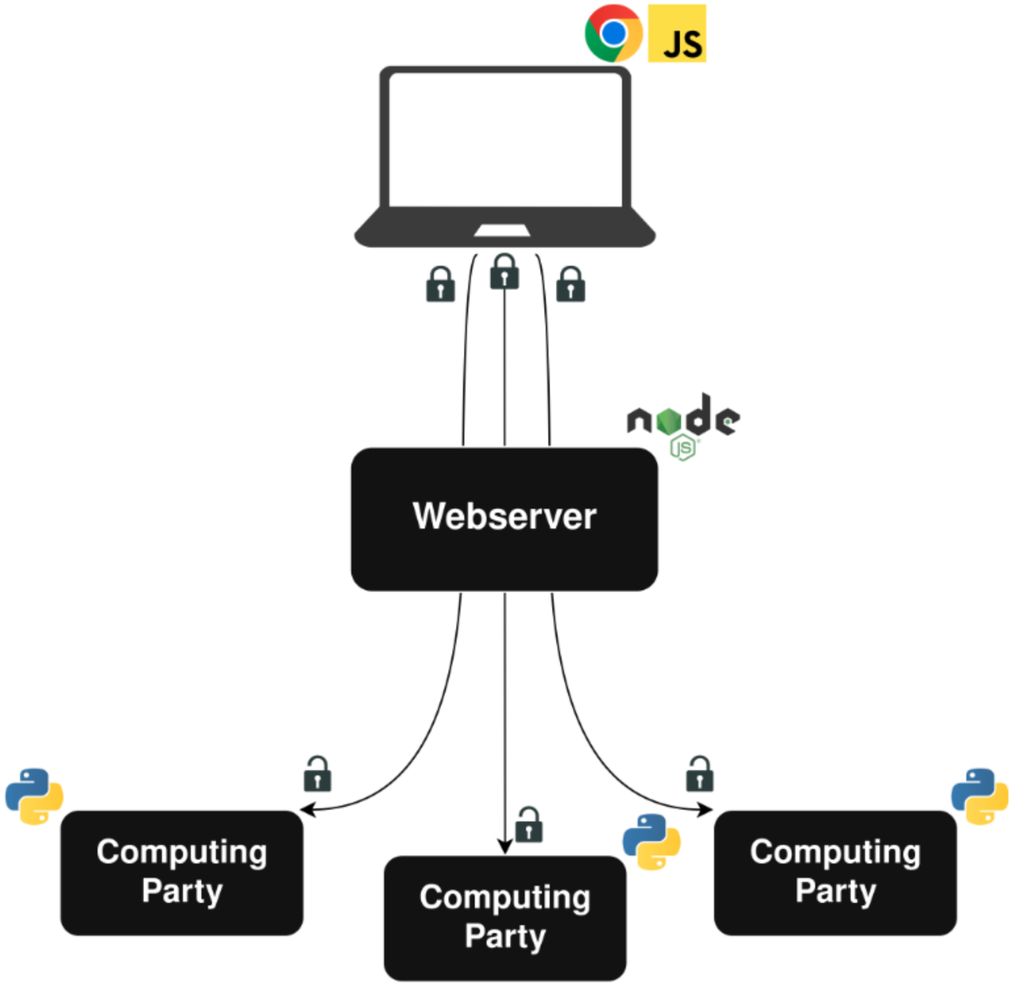

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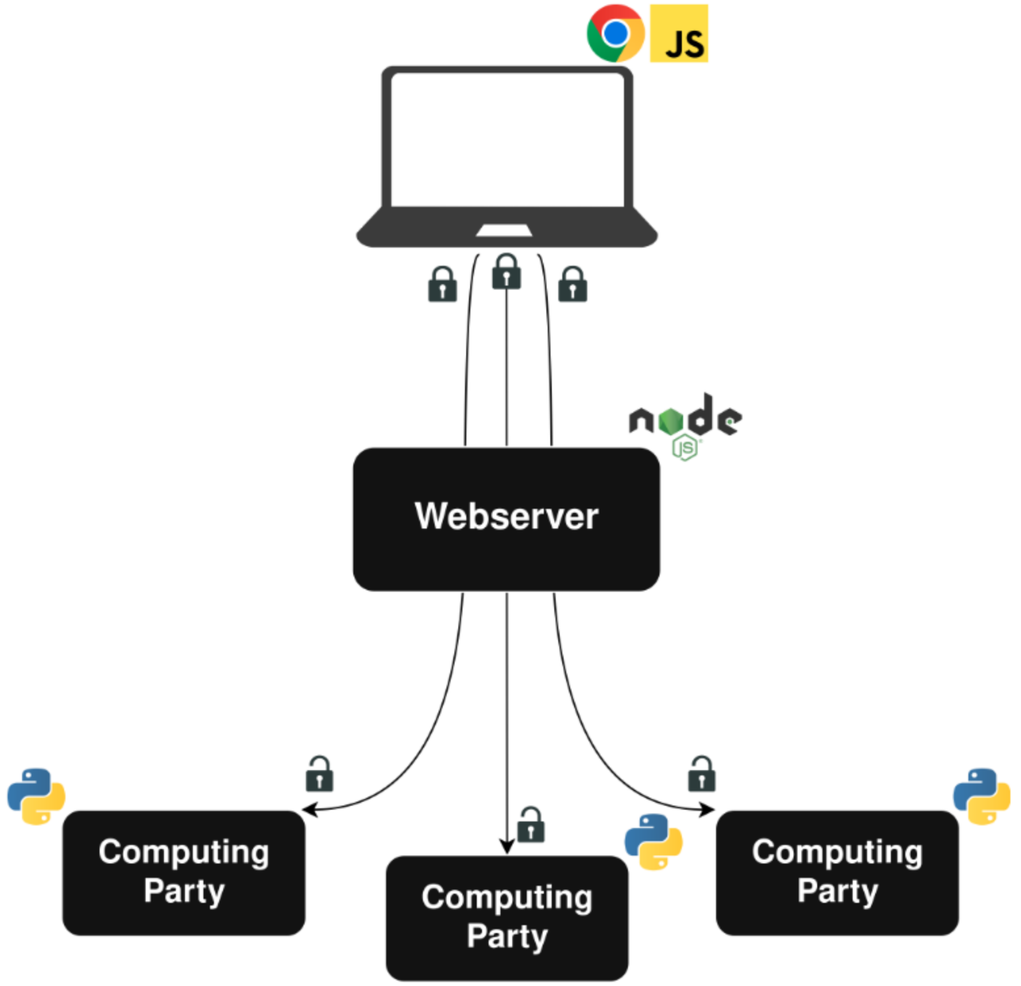
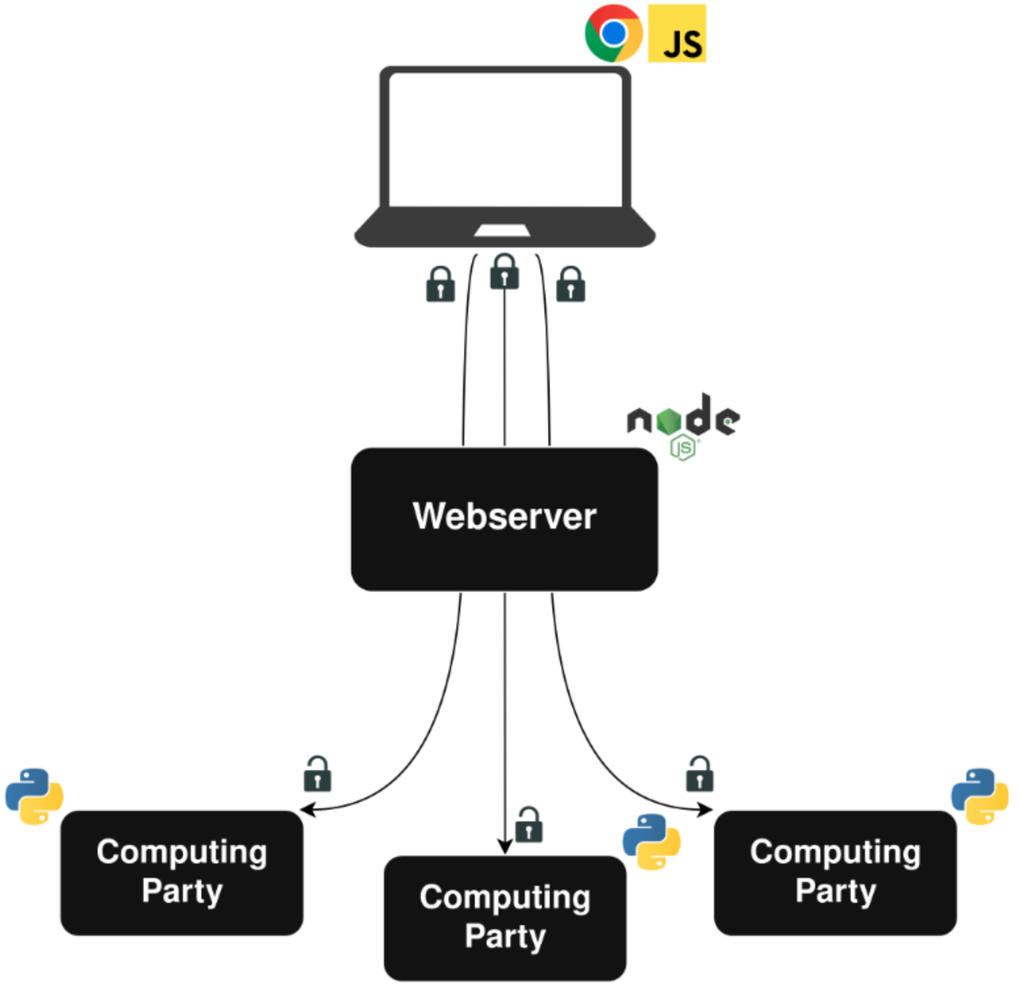


Webserver


JS
node
Webserver
Computing Party
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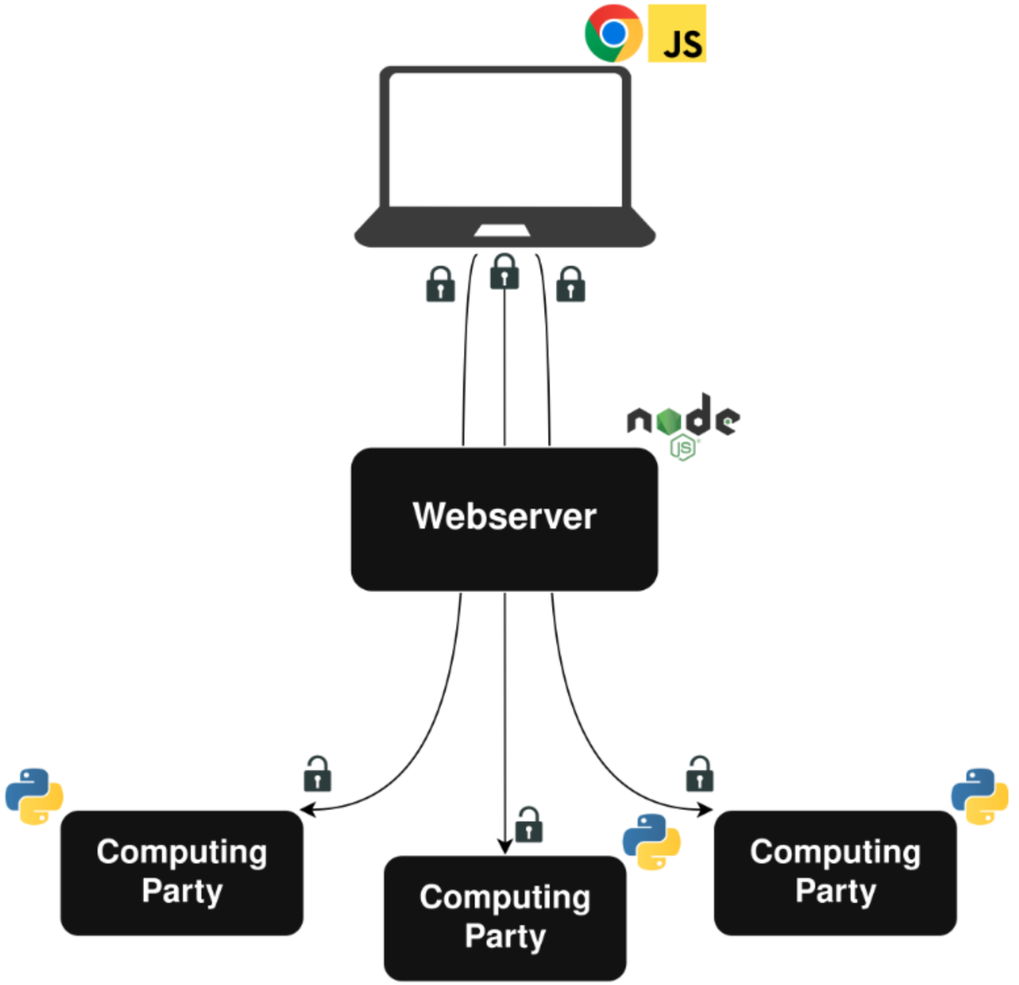
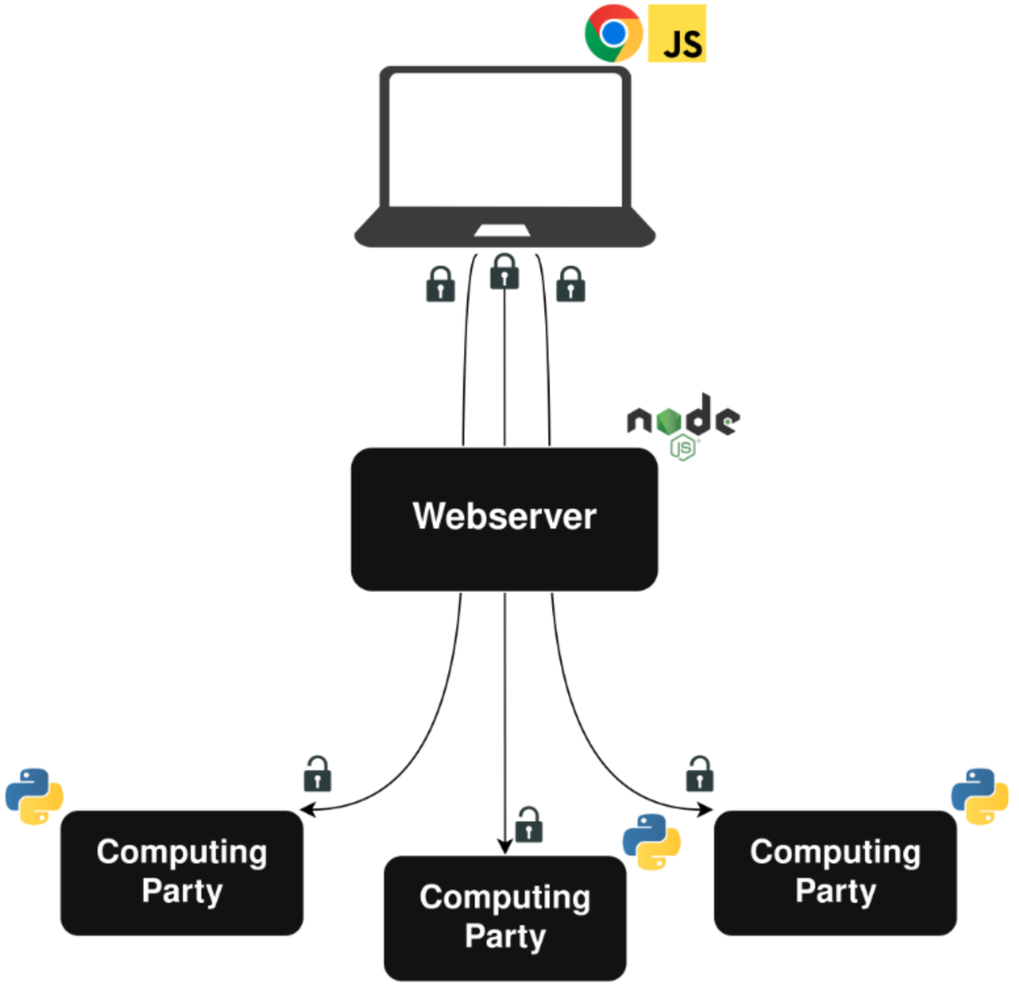
Webserver

- Simplifies interaction with clients



Webserver

- Simplifies interaction with clients
- Collects basic metadata



Webserver

- Simplifies interaction with clients
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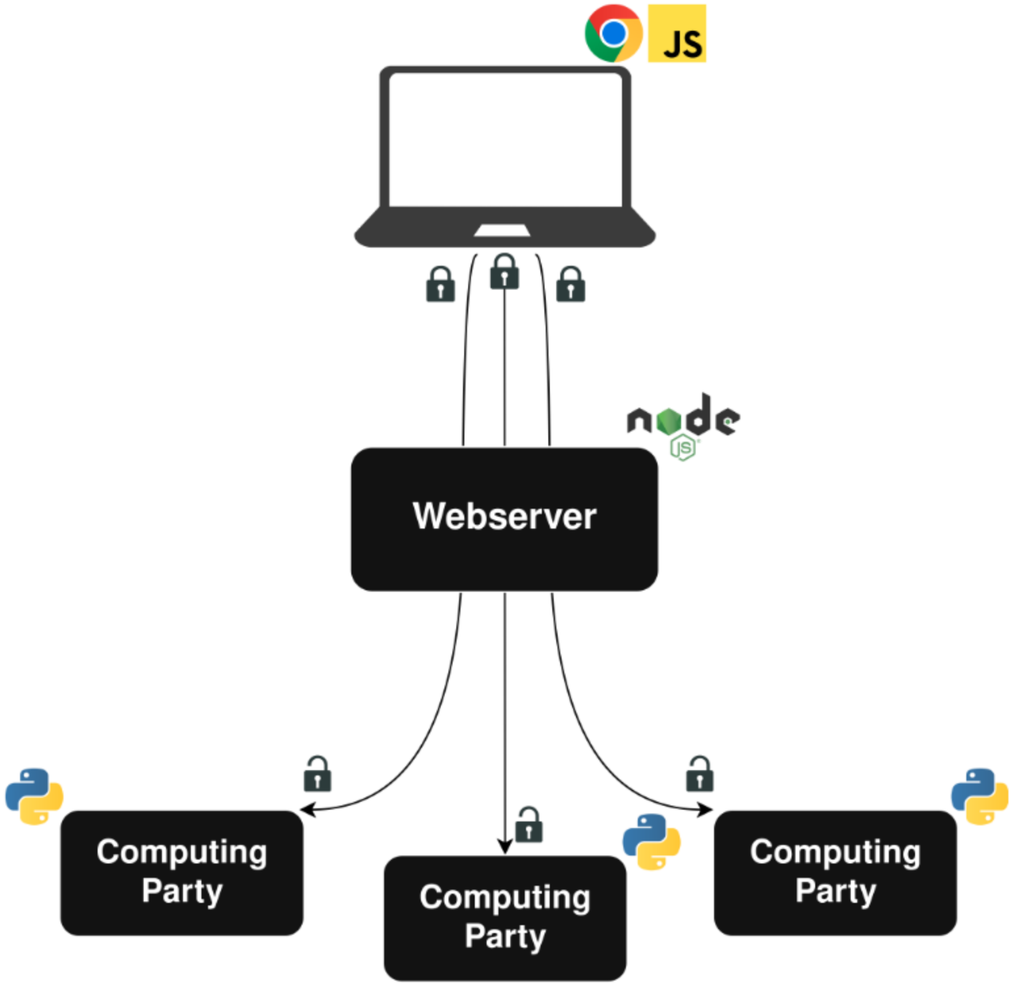

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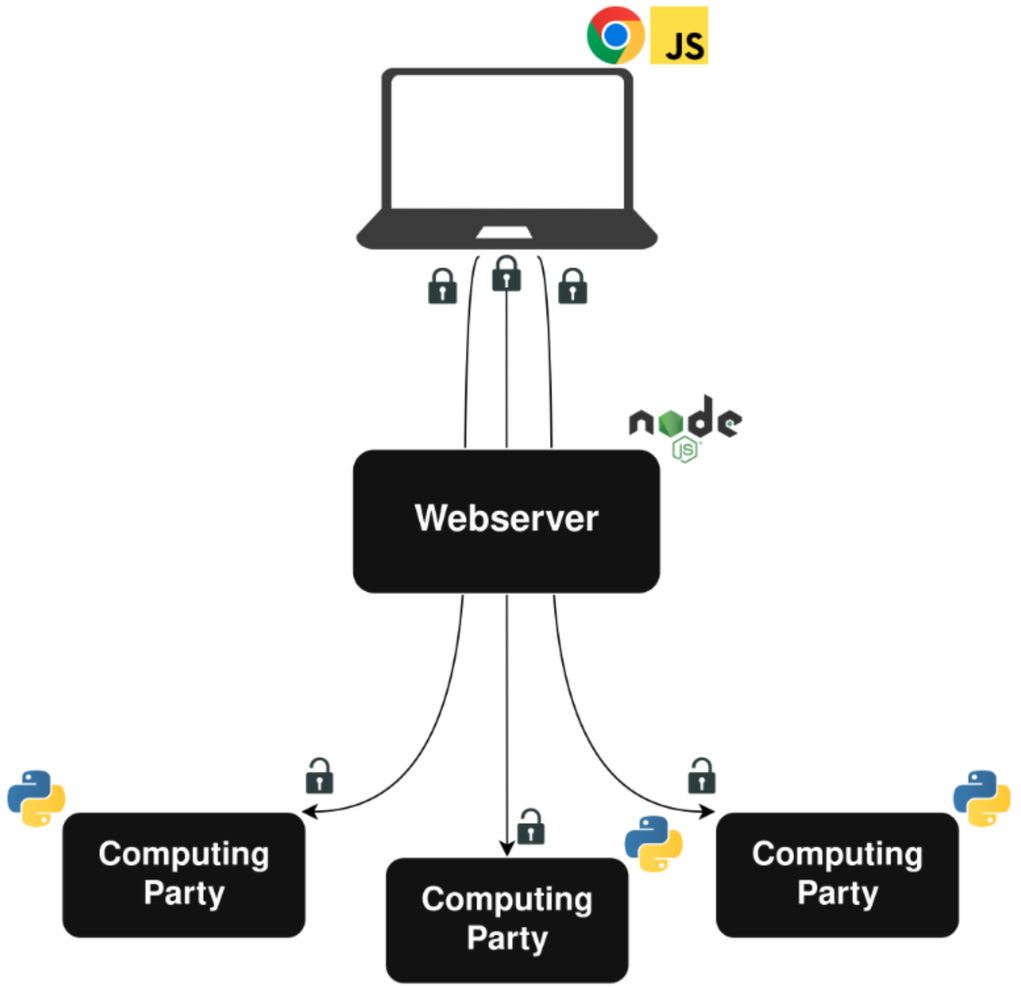

Webserver

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  - For payment and location tracking
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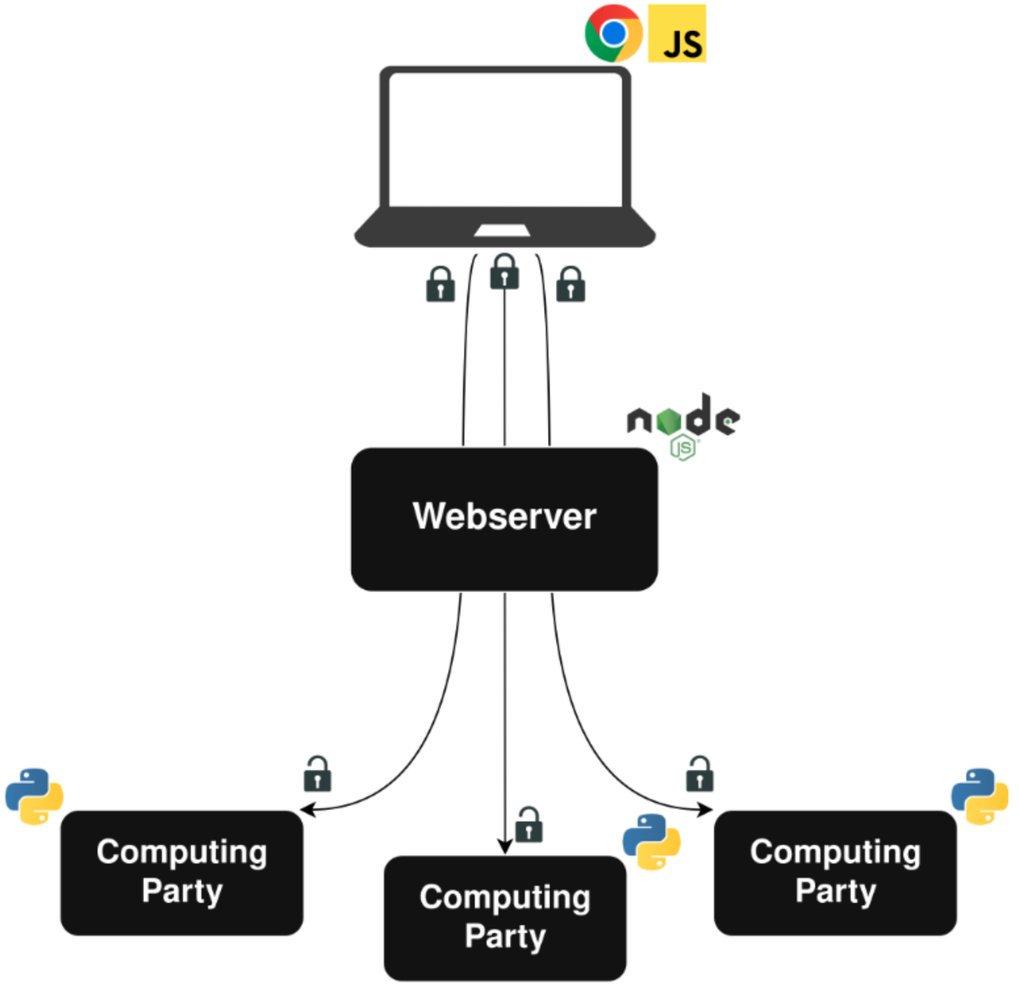
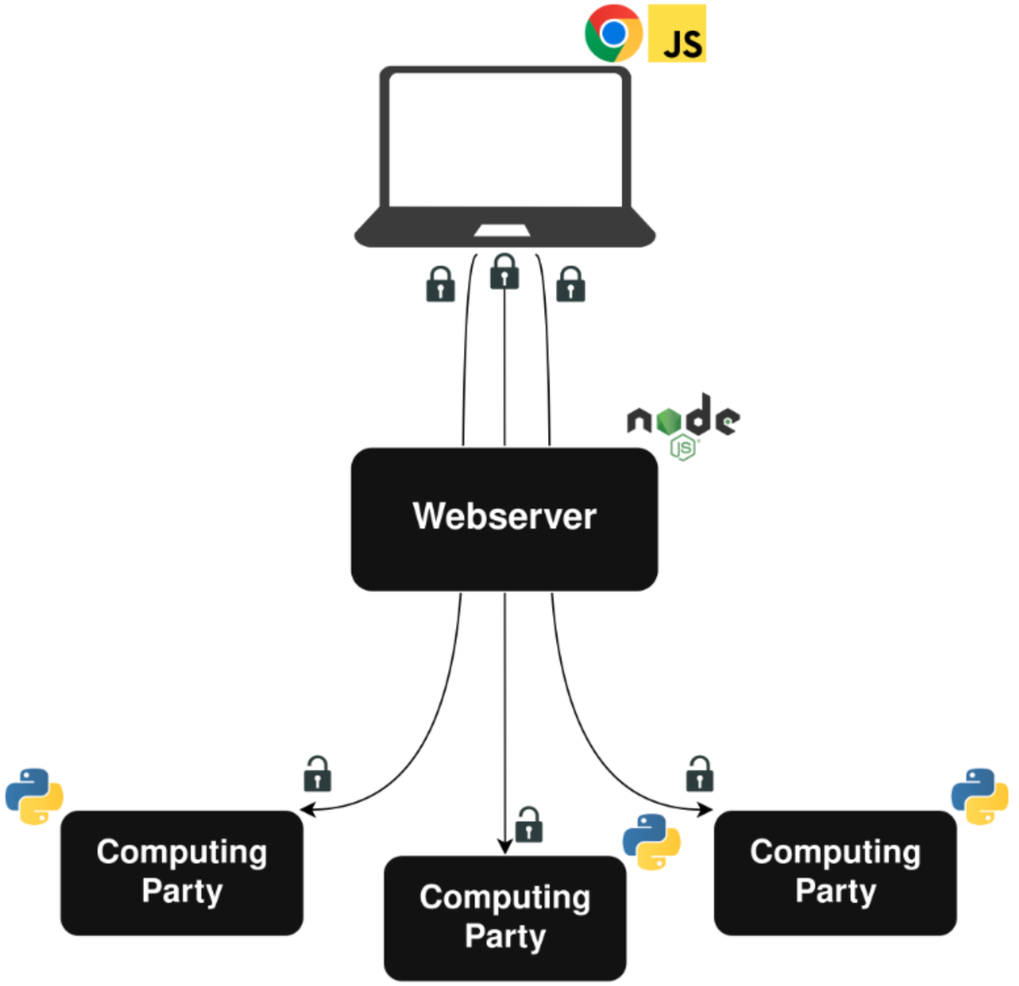
  - Secret-shares are end-to-end encrypted to the parties



MPC Backend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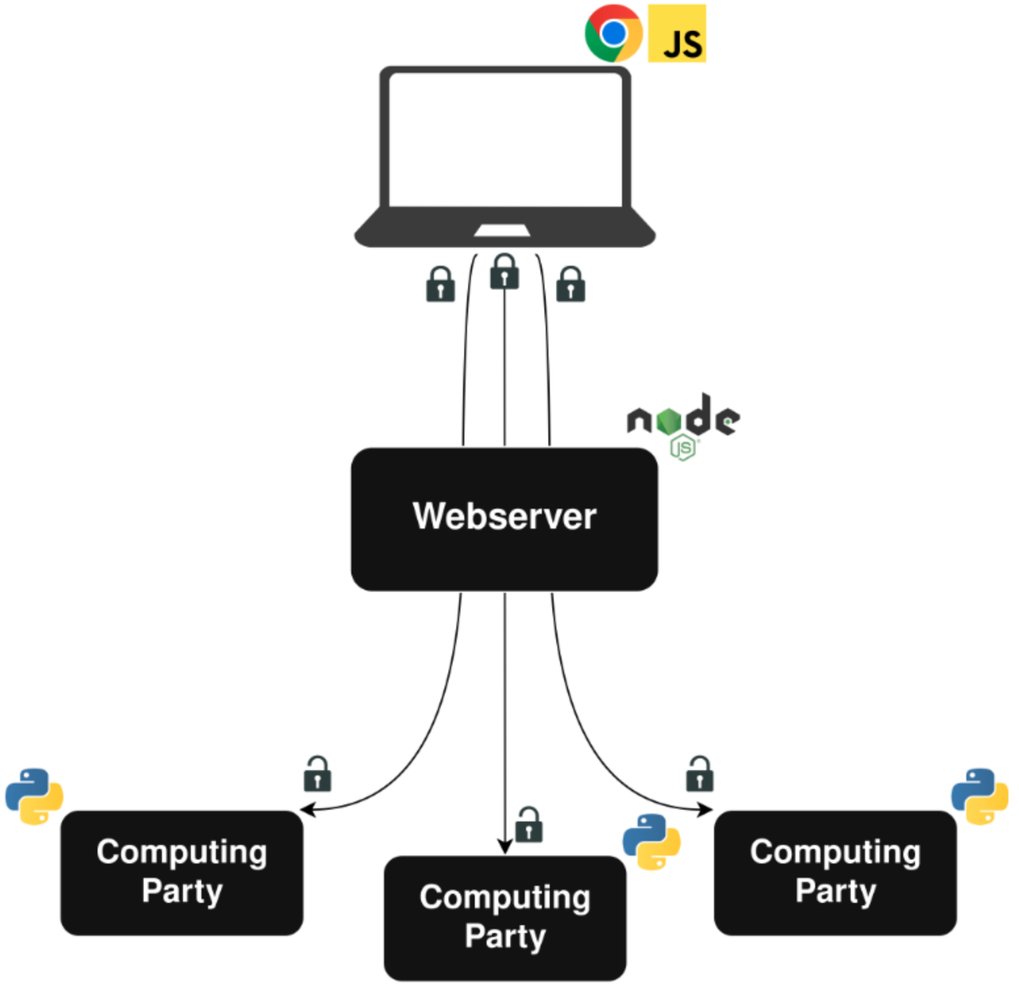
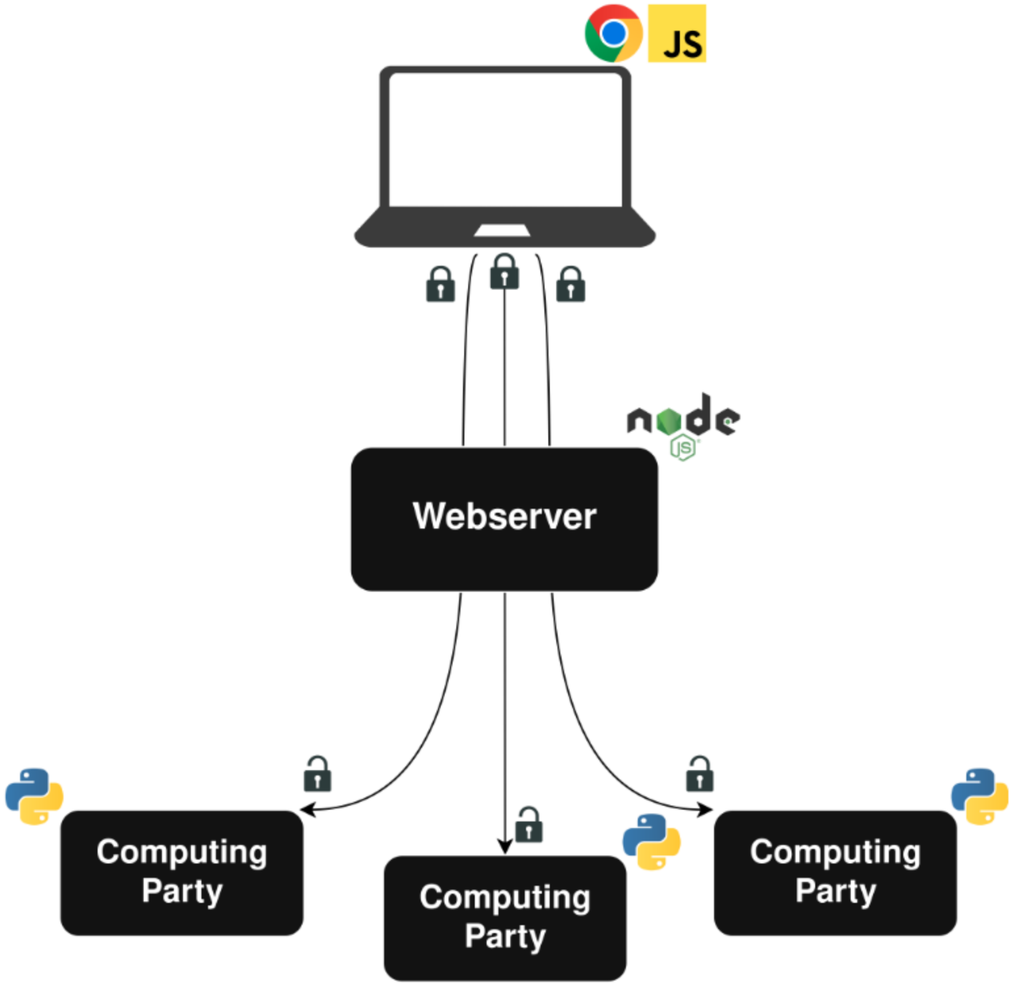
MPC Backend

- Threat model



MPC Backend

- Threat model
  - Three parties



MPC Backend

- Threat model
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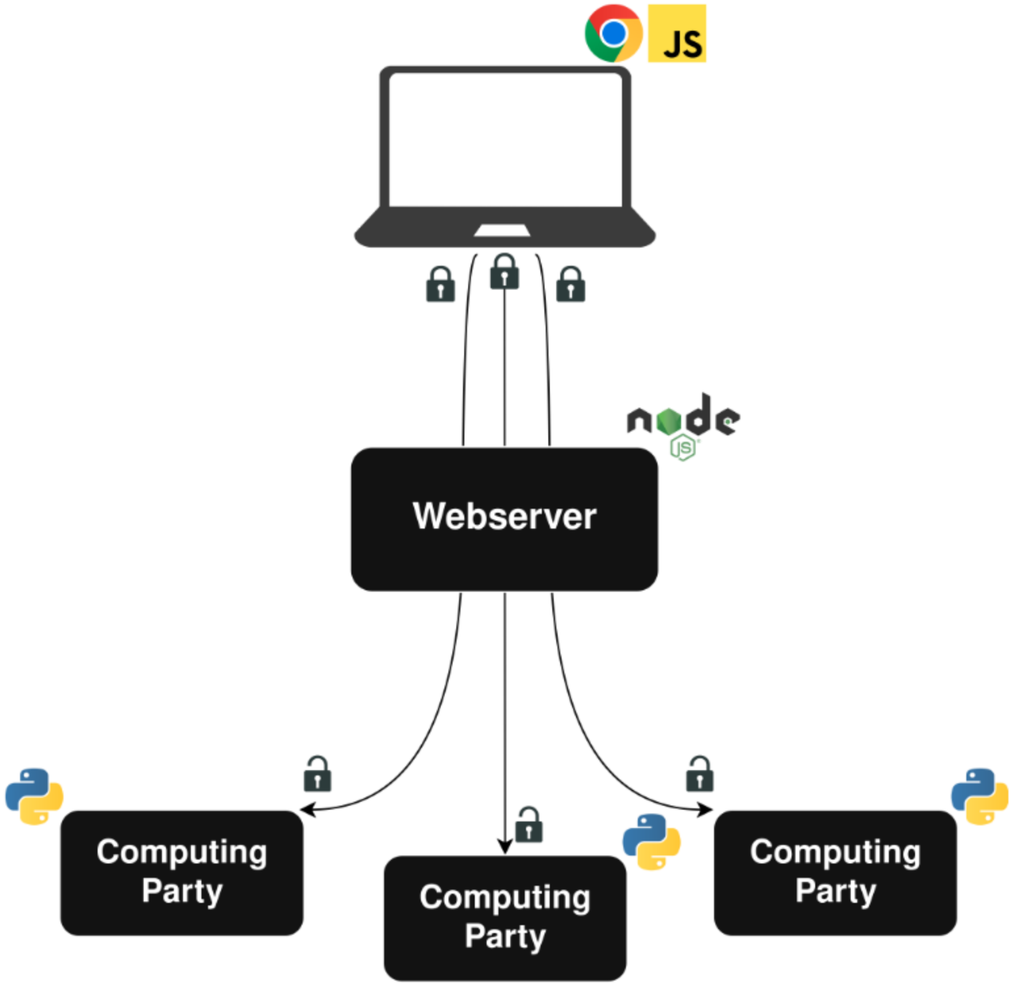
  - Semi-honest security



MPC Backend

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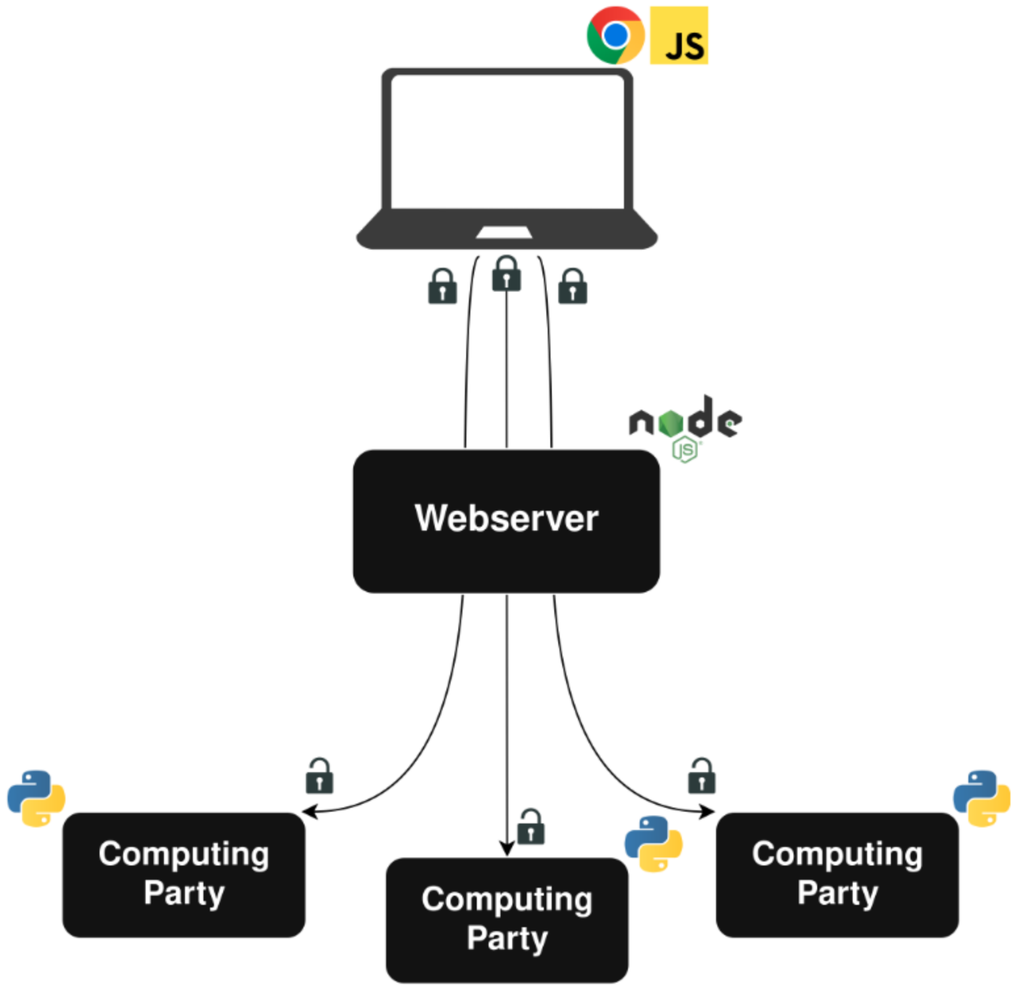
  - One adversary



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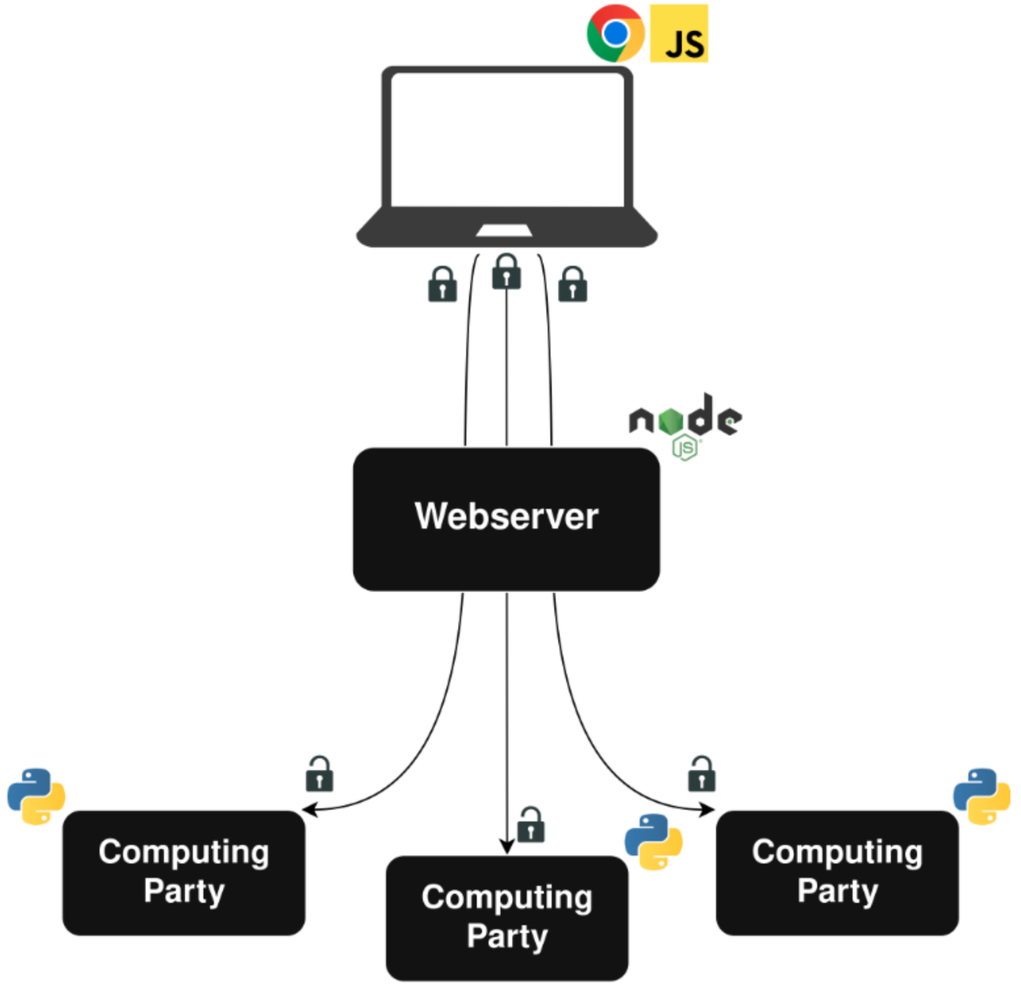

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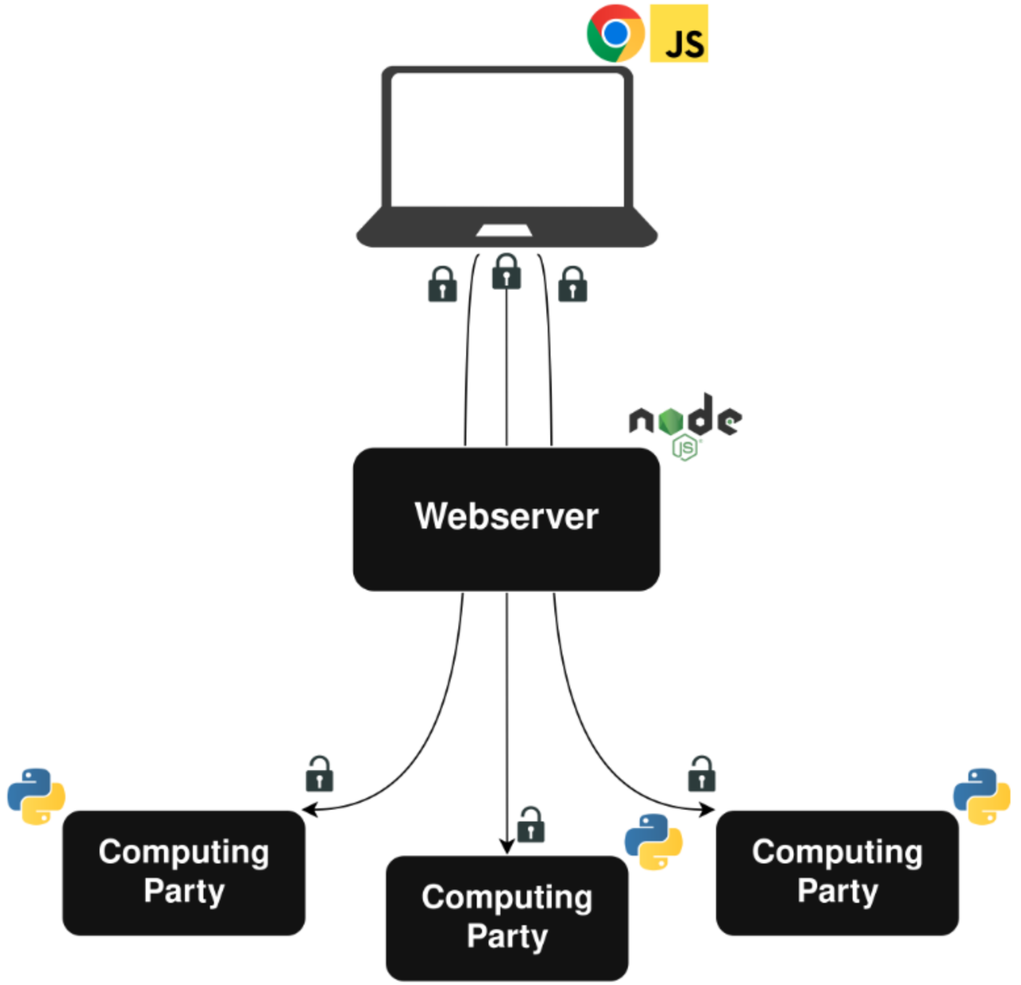
- Code will be available in the future



The Learning Process

Learning from Label Proportions (LLP)

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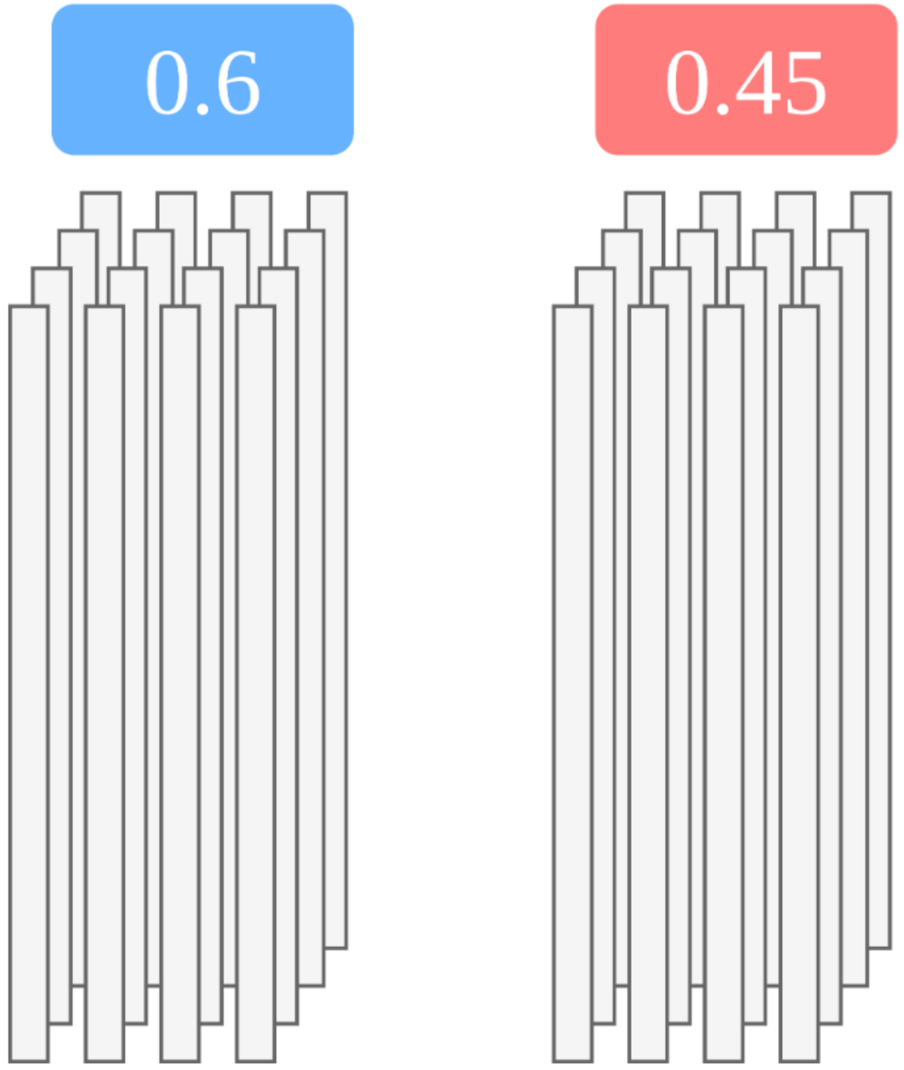

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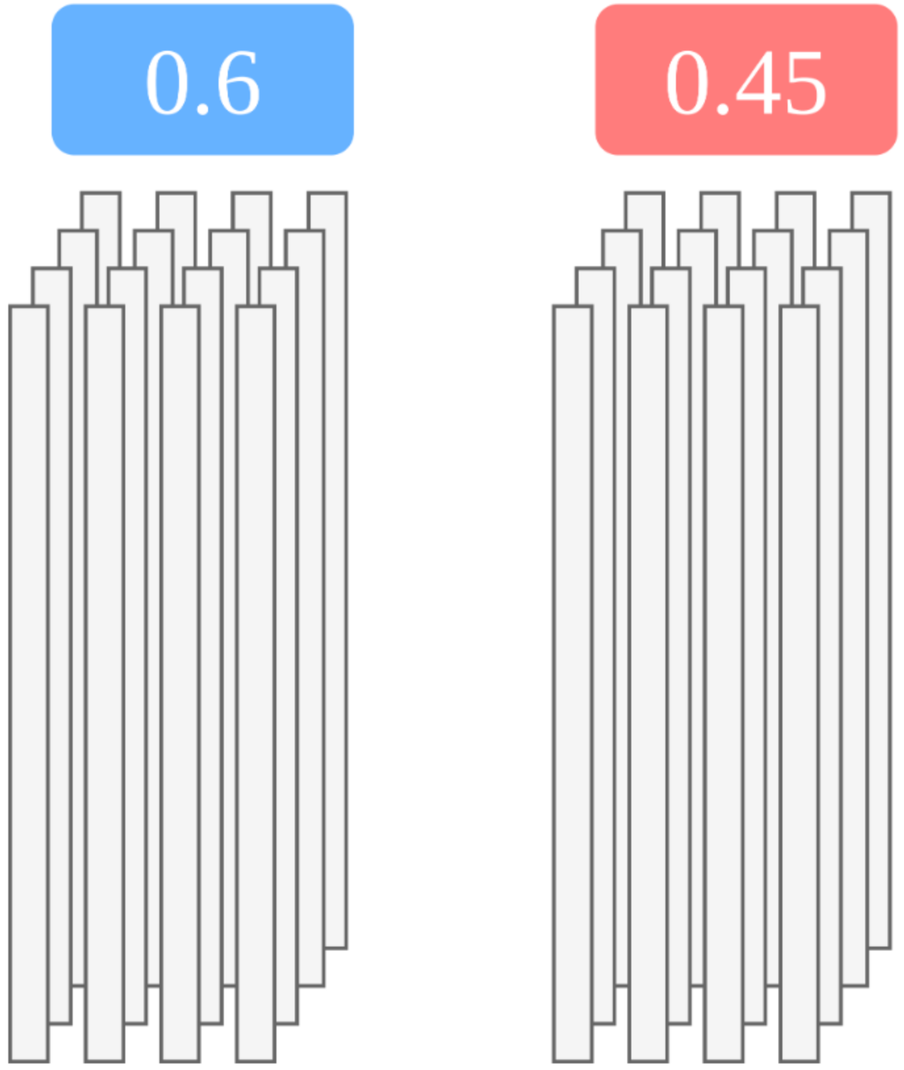

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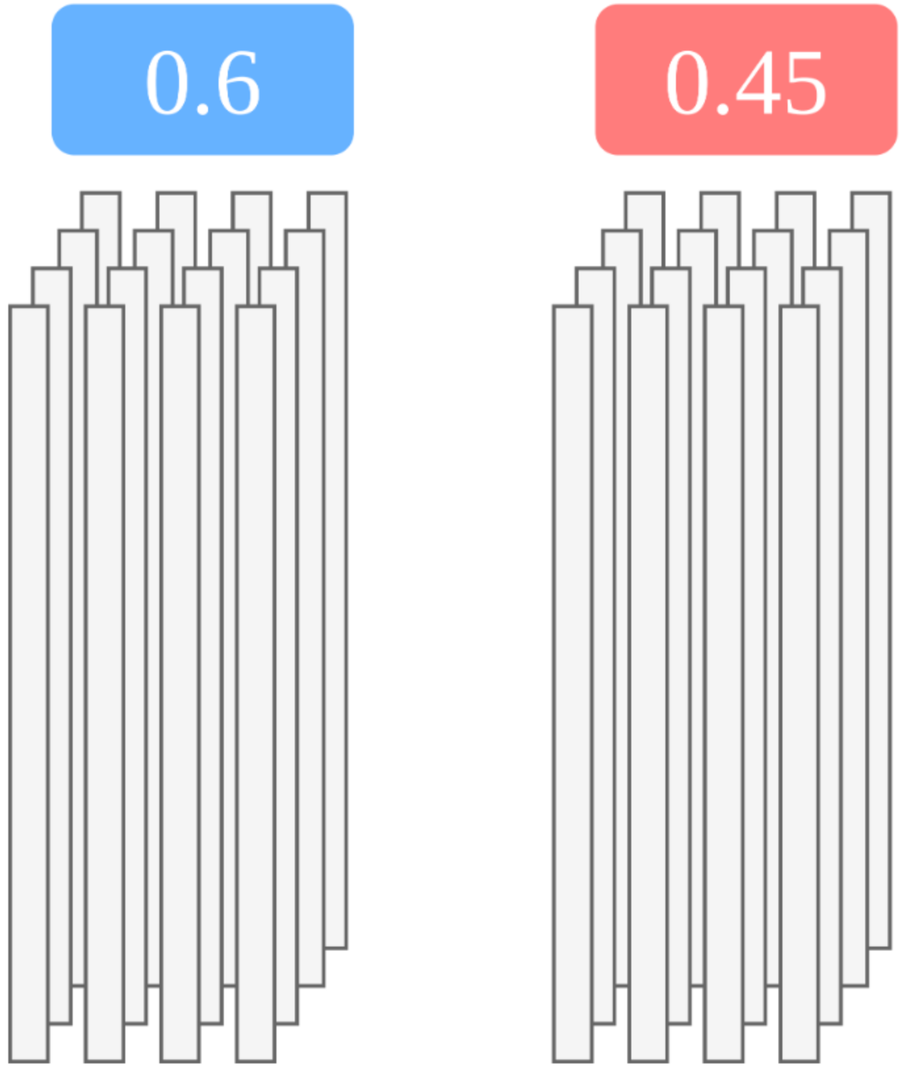

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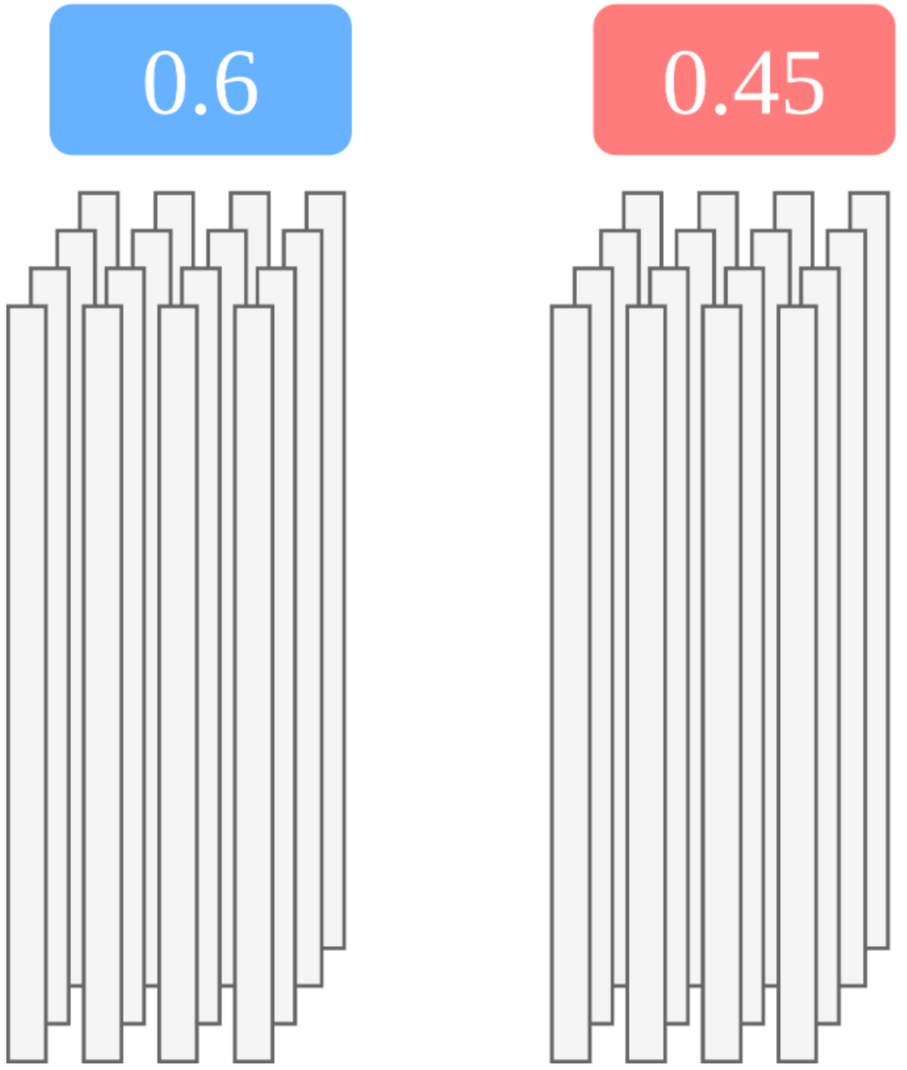

The Learning Algorithm

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Input: visit and referral histograms grouped by state, state-level ground truth

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Train–update loop until convergence

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- Assign initial predictions to each individual

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Lessons Learned and Future Directions

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Digging Deeper on the Data

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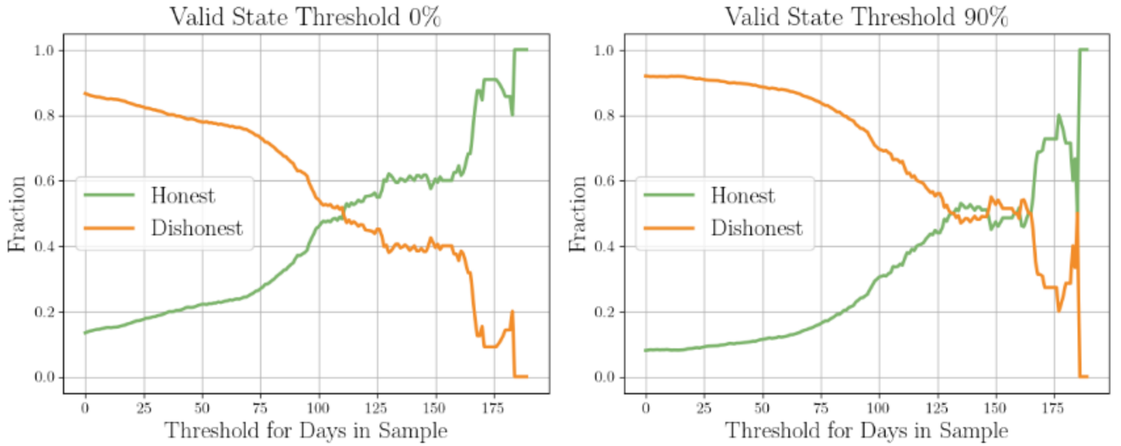

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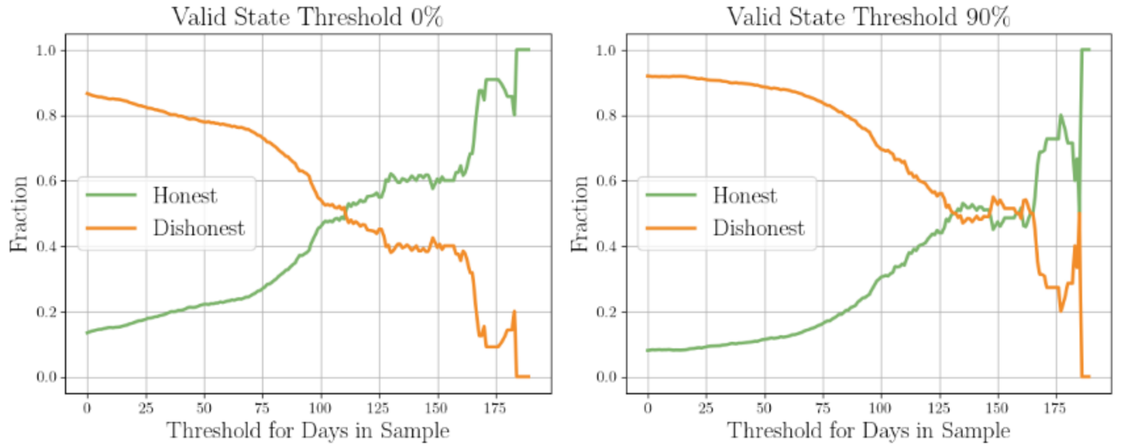

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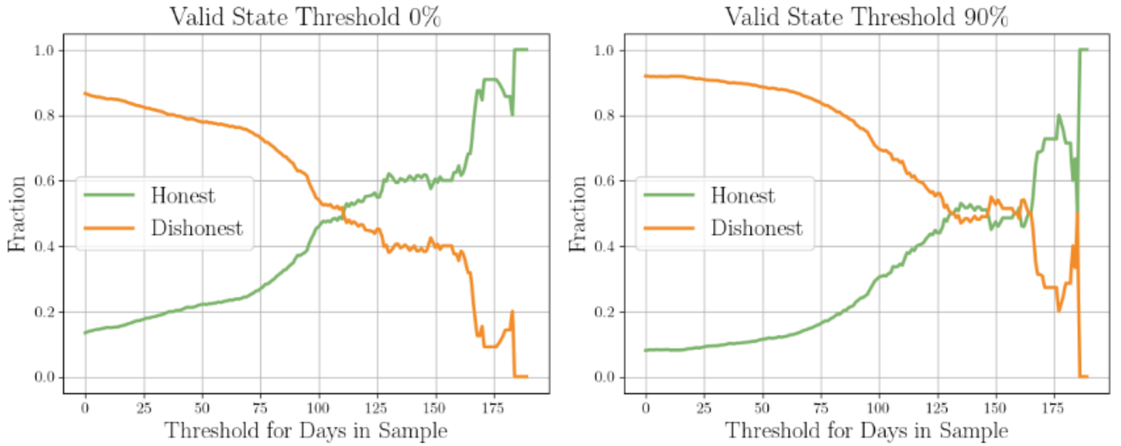

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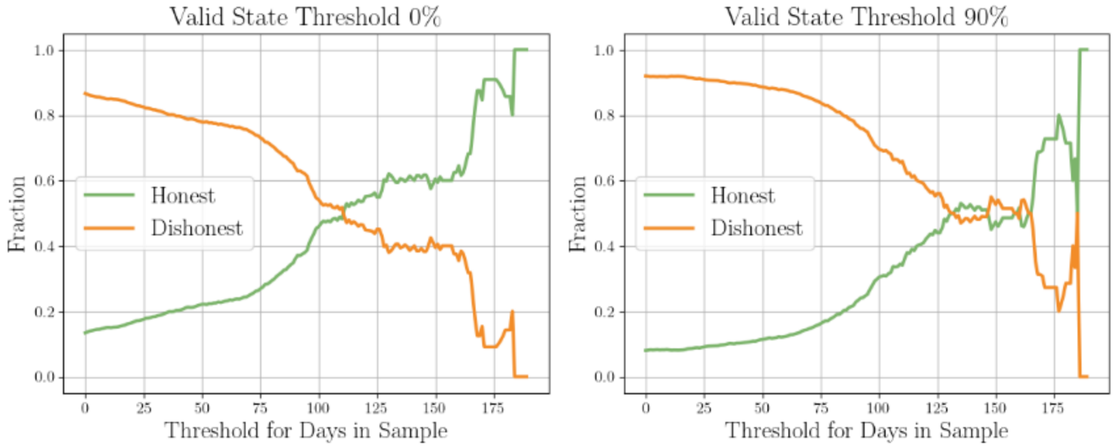

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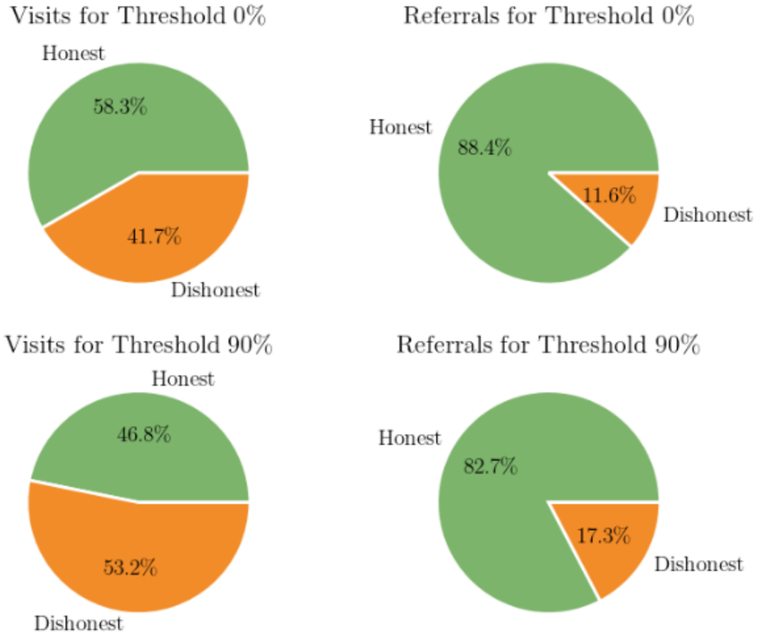

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- Integrate cryptographic techniques with existing plaintext approaches

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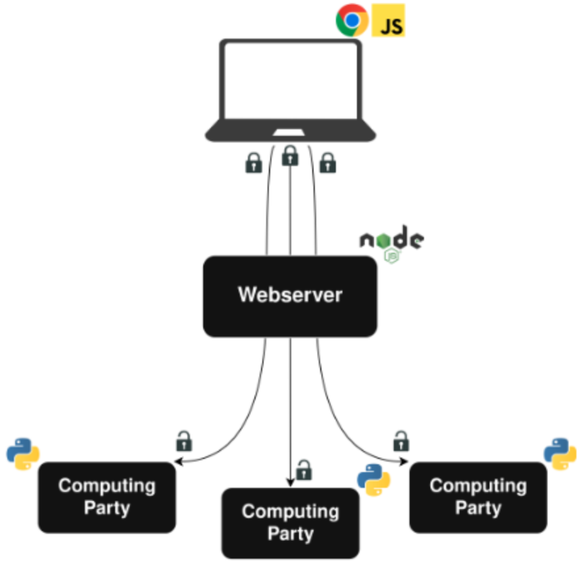

Thank You!

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